

Psychological Determinants and Consequences of Complex Networks

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Abstract

This paper presents two models that exemplify psychological factors as a determinant and as a consequence of social network characteristics. There is an endogeneity considered in network formation: while the social experiences have impacts on people, their current psychological states and traits affect network evolution. The first model is an agent-based model over Bianconi-Barabasi networks, used to explain the relation between network size, extroversion, and age of individuals. The second model deals with the emergence of urban tribes as a consequence of a smaller propensity to communicate with different with different traits and opinions.

1 Introduction

In recent years, there has been a strong upsurge in the study of identity as a variable, built up on different types of individuals' representation, also known as identity traits [20], dipped in a social logic with values and customs of the time. According to Social Comparison Process Theory [17], people unconsciously compare themselves with the ones who are similar to them, and this behaviour boosts social networking, thus contributing to life in society.

Natural phenomena can be usefully described in network terms. Sociologists have perceived the usefulness of this approach and several applications were developed [19, 6]. However, there is a link between behavioural sciences and the sociological realm lacking in the complex synthetic networks literature.

Some models are very successful in modeling real social networks [23]. Some factual characteristics like the higher probability of meeting a friend of a friend than a complete unknown were observed and realistic networks emerged. This is in the sociological realm. Not to consider behavioural questions is not a flaw as they would not increase the explanatory power of the macro level as they

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would increase the complexity of the model. However, some questions about the nature of the agents are not noticed in this perspective.

On the other hand, sociophysics are an important stream of research in quantitative methods for sociology [18, 31] and can be used to understand this. Through simple rules, such as the ones used in the Sznadj Model [34] and Kynetic Exchange Opinion Models [25], real phenomena isolating important characteristics are explained. Within this reseach area, variations dealing with extremism or contrariness [27, 12] represent a movement towards a more plausible modeling from a psychological perspective. For instance, [27] presents a model with the intransigence of an agent being endogenous.

This trend represents an important theoretical step. Past empirical research has shown that the location of a person in a social network can predict personality traits of big-five factors [10]. On the other hand, there is evidence that the psychological traits of agents may affect how their networks is [33], showing some endogeneity. Applications acknowledging this direction are fruitful in political science and migrations [26, 29]. In management, it was shown that narcissism can play a strong role on a CEO’s decision making, in a sense that higher levels of narcissism leads to weaker inclination for following past directors’ strategies [9, 37].

In this paper, we propose to fill this gap through a theoretical sociophysics model that considers the endogeneity between node preferences and traits — the fitness of a node in Bianconi-Barabasi networks [5] — and the structure of the network. Two models incorporating this idea are developed. First, a simple reinforcement learning paradigm affects the “social expertise” of the agent over a network and this affects how this network is developed. An application to the results presented at [30] is presented.

The second model deals with the emergence of urban tribes as a function of the willingness to communicate with different persons — modeled as a bounded confidence model [22, 14] — and the decay of the social relations. These parameters can explain the number of groups that emerge over time and in the stability of groups over time. This is useful to illustrate the sociological and microeconomic literature on identity and behavior [2].

This model may be compared with Axelrod culture model [3]. In this previous model, the diffusion of culture is ran over a static structure with the culture being discussed over it. In one hand, Axelrod model is appropriate to real situations where it is not possible not to isolate people easily. However, in social networks based on individuals, like online social networks, it is easier to avoid unwanted people and reconfigure the edges structure. This leads to groups that interact, but not necessarily have the same opinion, and usually

In the second section the reinforcement model is developed and discussed. The third section introduces the urban tribes model. Finally, some remarks about the models are made and the conclusion is presented.

2 Baseline Model

Reinforcement learning is an important tool for cognitive architectures [35], modeling habits [21] and solving games [16]. To model the behavior of an agent over a complex network, it is important to consider that her aptitude to create contacts or to keep relations is a function of some psychological states that may

be reinforced.

In a simple example, some would expect that social stigma would lead to low self-esteem. This relation is attenuated by the usage of in-group support to reinforce the self-esteem of the members [11]. However, there is strong evidence that minorities suffer from effects that majorities do not [28]. The possibility of suffering bad experiences must be considered in this reinforcement model.

Bianconi-Barabasi networks [5] are important in this context as they have a fitness parameter for each node that in social contexts may represent the presence of a socially valuable characteristic. However, to only consider a fixed fitness is not related to the reinforcement learning paradigm. An alternative is to update the fitness following some pleasant experiences, rewarding the agents that participated of the experience.

The experiences are inspired in a Kinetic Exchange Opinion Model [25] paradigm: randomly an edge between two agents is selected and the participants of it have a fitness increase after a round of interactions. The fitness function may be variable. In this initial model, it is a realization of an Bernoulli distribution: with probability p it is positive and with possibility $1 - p$ it is negative. The cases tested were $p = 1$ and $p = 0.5$.

Another question which is important in this initial model is the structure between sample size, time periods and interactions per time period. The smaller the sample size to interactions ratio, the less the agents — independently of fitness — are inexperienced. The time period, in this case, it is just a measure without much interpretation besides regulating the learning of the agents. What is really important for the agents is this ratio that may be understood as the age of the agents.

Algorithm 2.1: NETWORK1(*SampleSize*, *Shocks*, *Time*)

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Fitness  $\leftarrow$  ones(SampleSize)
for  $i \leftarrow 1$  to Time
     $\left\{ \begin{array}{l} \textit{Network} \leftarrow \text{Barabasi-Bianconi}(\textit{fitness}) \\ \textit{Experience} = \text{zeros}(\textit{SampleSize}) \end{array} \right.$ 
    for  $j \leftarrow 1$  to Shocks
        do  $\left\{ \begin{array}{l} \text{Select randomly an edge}(a, b) \\ \text{do } \left\{ \begin{array}{l} \textit{Experience}(a) = \textit{Experience}(a) + \textit{reward} \\ \textit{Experience}(b) = \textit{Experience}(b) + \textit{reward} \end{array} \right. \\ \textit{Fitness} \leftarrow \textit{Fitness} + \textit{Experience} \end{array} \right.$ 
    return (Fitness)

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The algorithm for this model is presented in Algorithm 2.1. It details how the baseline model simulations are performed. The results of simulating this process a thousand times considering the initial fitness an $1 \times N$ unit vector, with a reward of 0.05 can be seen in figure 1.

Figure 1 presents two simulations that have different characteristics. The first simulations varies the “sample size to interactions” ratio. The main result considering this variation is that the higher the “size to interactions” ratio, the smaller the average fit. If we keep this ratio fixed, the average fitness is similar for all the sample sizes. However, the average ratio between the maximum individual fitness and the median individual fitness is higher for large samples.

The maximum to minimum ratio, the maximum to median ratio and average

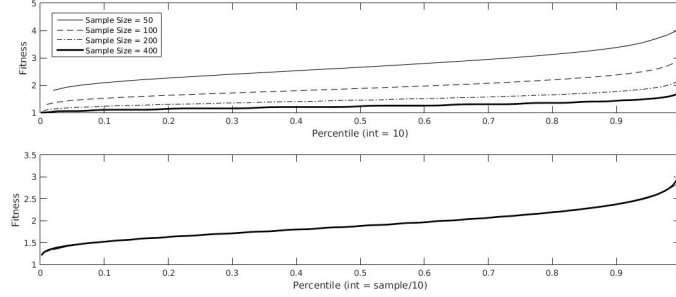


Figure 1: The simulations with initial fitness equal to 1 and rewards fixed and equal to 0.05. The fixed number of shocks leads to distortions in the mean of the fitness. The higher the “size to interactions” ratio, the smaller the average fit. In a fixed “size to interactions”, the higher the sample size; the higher the distance from the maximum individual fitness to the median fitness.

Sample Size	Iterations				Sample to Interactions			
	N=50	N=100	N=200	N=400	N=50	N=100	N=200	N=400
Average Fit	2.7232	1.9266	1.4810	1.2452	1.9347	1.9266	1.9227	1.9205
	0.0130	0.0055	0.0021	0.0008	0.0073	0.0052	0.0039	0.0026
Maximum to Median	1.5204	1.5787	1.5493	1.4596	1.5233	1.5795	1.6337	1.6932
	0.0870	0.0984	0.0940	0.0876	0.1069	0.0980	0.0944	0.0915
Maximum to Minimum	2.2553	2.3090	2.1124	1.7942	2.1671	2.3072	2.4554	2.6114
	0.1989	0.1908	0.1462	0.0958	0.1948	0.1871	0.1815	0.1734

Table 1: Means and standard deviations for the simulations presented in Figure 1. It is important to perceive that considering the sample size to interactions ratio fixed, the average ratios between the largest individual fitness and the other metrics are larger.

fitness are in table 1. The averages and standard deviations for a thousand simulations are exhibited and confirmed in the results from figure 1.

The results exhibited here are valid in a context where the payoffs of an interaction are positive. However, in real life there are little cases where all the interactions within a group are positive and some social interactions may result in clashes between individuals. The model adapts itself to this fact by changing p to a probabilistic case.

Setting $p = 0.5$, the results are present in figure 2. In these simulations the fitness of an agent is never below 0. This figure shows that the fixed number of shocks does not create a distortion with different averages for different samples sizes this time. With probabilistic rewards, a higher “size to interactions” ratio leads to a higher maximum individual fitness to the median fitness as well a high sample size. Table 2 condenses this information.

In table 2, it is possible to see that for a high sample size to interactions ratio — including the one fixed — there are some maximum to minimum ratios that are non-estimated due to non defined elements. Considering only the maximum to median ratio, the effect is similar to the observed in table 1 for the “Sample to Interactions” parameters.

While this model is not very complex, it can give some insights. For instance, table 1 is useful when analysed with the results of [30]. In Roberts *et al.*

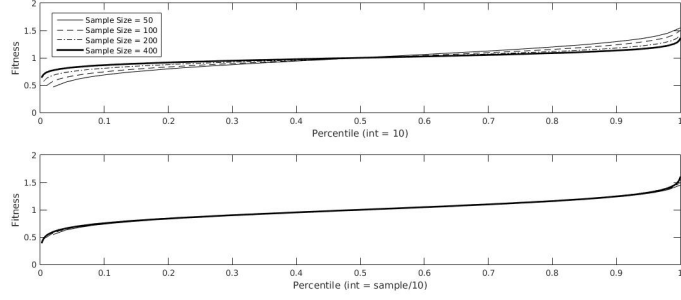


Figure 2: Simulations with initial fitness equal to 1 and rewards fixed and equal to 0.05 and varying rewards. The fixed number of shocks does not lead to different averages for different samples sizes this time. However, a higher “size to interactions” ratio leads to a higher maximum individual fitness to the median fitness. Considering this ratio fixed, the higher the sample size, the higher the distance from the maximum individual fitness to the median fitness.

Sample Size	Iterations				Sample to Interactions			
	N=50	N=100	N=200	N=400	N=50	N=100	N=200	N=400
Average Fit	1.0060	0.9969	0.9963	1.0003	0.9970	0.9981	0.9991	0.9996
	0.1708	0.0942	0.0492	0.0246	0.0987	0.0917	0.0927	0.0934
Maximum to Median	1.5488	1.5050	1.4232	1.3498	1.4573	1.5009	1.5508	1.5936
	0.1558	0.1056	0.0773	0.0600	0.1155	0.0994	0.0961	0.0935
Maximum to Minimum	-	-	2.5880	2.0972	-	-	-	-
	-	-	0.6433	0.2405	-	-	-	-

Table 2: Means and standard deviations for the simulations presented in Figure 2. The maximum to minimum ratio was not considered for some cases due to null individual fitness cases. Considering the maximum to median ratio, the effect is similar to the observed in table 1 for the “Sample to Interactions” parameters.

paper, both network size and age are correlated with Extroversion (measured by psychometric scales). When the authors considered age as a variable to explain network size, the significance of extroversion was vanished. In line, our results show that more interactions — small sample size to interaction ratio — lead to higher means in the traits. In other words, there is a correlation between number of interactions and trait, but trait itself is built over accumulation of interactions.

3 Tribes and Communications in Networks

Previous models have not yet analysed the memory of the networks. We consider that, for each iteration of the algorithm, the network is restated. In other words our model considers a set of nodes shared across the time instead of a temporal network. Moreover, the algorithm implicitly assumes a pool of acquaintances, in which active relations are developed each turn. In sum, although our model still provides understandings about how psycho-social characteristics and synthetic network characteristics may be linked, it is not fully developed as a valid network.

An alternative is based on the rewiring of a graph [36]. Each time period, an edge ab has the probability q of being rewired. This technique, however, yields two questions: 1) how to calculate q (or must it be a constant?); 2) how to keep preferential attachment and realistic assumptions about connections?

In social psychology and social network research, there is a tendency to model less contacts with a decay on relationships that are not activated [7, 8]. This must be incorporated by the model: the passage of time leads to higher probability of forgetting.

However, in some sense, forgetting may be realistic if in a situation of rewiring the agent forgot a very similar friend by chance. This agent will possibly be missed, then a re-connection with a higher level of connection is plausible. If this peer is not close to you in the themes you like, then you may rewire to another person. Therefore, the mechanism to answer (1) is the same that is necessary for (2).

A mechanism of decay for q is to consider:

$$q_t^* = \alpha^{1-n} q_{t-1} \quad (1)$$

where n is the number of successful interactions. To this equation become $q(t)$, it is necessary to truncate values larger than zero. If the agent forgets an edge, then it must select a new (or the same) peer that now is a contact with $q_{t+1} = 1$. The preference for a new partner is a function of the difference between fitness:

$$w_{ij} = \frac{1}{1 + |fitness_i - fitness_j|}, \forall j \in \mathcal{S} \quad (2)$$

$$r_{ij} = w_{ij} \#Edges_j \quad (3)$$

where \mathcal{S} is the agent space and the selection of a new partner follows a Bianconi-Barabasi preferential attachment using w_{ij} instead of the fitness.

The concept of successful interaction used is based in the bounded confidence with threshold ϵ . Given an agent a in an interaction with another agent b , the fitness is updated following:

$$fitness_{at} = \begin{cases} \frac{fitness_{at-1} + fitness_{bt-1}}{2} & \text{if } |fitness_{at-1} + fitness_{bt-1}| \leq \epsilon \\ fitness_{at-1} & \text{else} \end{cases} \quad (4)$$

Synthesizing the model, the algorithm for this network is in Algorithm 3.1.

Algorithm 3.1: NETWORK2(*SampleSize*, *Shocks*, *Time*, *Alpha*, *Epsilon*)

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Fitness  $\leftarrow$  randn(SampleSize)
 $\left\{ \begin{array}{l} \text{Network} \leftarrow \text{Barabasi-Bianconi}(\text{ones}(\text{SampleSize})) \\ q = \text{ones}(\text{SampleSize}) \\ \text{for } i \leftarrow 1 \text{ to } \text{Time} \\ \quad \text{do for } j \leftarrow 1 \text{ to } \text{Shocks} \\ \quad \quad \text{do } \left\{ \begin{array}{l} \text{Select randomly an edge}(a, b) \\ \text{Update edges } fitness_a \text{ and } fitness_b \text{ according to equation 4.} \end{array} \right. \\ \quad \text{Update } q \text{ following equation 1.} \\ \text{Dead} \leftarrow q < \text{RandomVector}(\text{SampleSize}) \\ \text{for } j = 1 \text{ to } \text{SampleSize} \in \text{Dead} = 1 \\ \quad \text{do } \left\{ \begin{array}{l} \text{Rewire according to equation 3.} \\ q_j = 1 \end{array} \right. \\ \text{return } (Fitness) \end{array} \right.$ 

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This algorithm generates networks that have as a property a control over the number of groups that appear after some interactions. More clearly: variations of ϵ lead to an ambient with more or less groups defined. In sociological terms, low disposition to talk with different persons implies in more stable groups that do not connect and convince each other about similar topics (leading to non-unanimity).

Another consequence of low ϵ is the reduced number of relations that are durable. The agents frequently peer contacts that are not similar as they want, therefore q decay frequently. This is exhibited in figure 3, simulated with Sample Size equals to 80, number of shocks fixed at 10, $\alpha = 0.9$ and initial fitness generated from a standard normal distribution. This is robust to variations of α .

It is interesting to notice that this may be related to polarisation on social networks. The easiness to ignore or unfollow other people may reduce the tolerance to some debates. Imagining the relations between fitness as a social distance parameter [1], some people may have less desire for a given element of that group. A slightly smaller fitness may isolate them from more radical people and so on, progressively. Some graphs generated by this algorithm are displayed in figure 4a and figure 4b using a population of 40 nodes. Other parameters were set as 20 shocks per turn as $\alpha = 0.99$, so the death of nodes is relatively rare. Even in this case, the graph be broke in two non-connecting networks.

This phenomena is due to the propensity of connecting to people that has similar opinions — fitness — over the out-group. This can be analysed by changing equation 2:

$$w_{ij} = \begin{cases} 1 & \text{if } |fitness_i - fitness_j| < \epsilon \\ a & \text{else} \end{cases} \quad (2b)$$

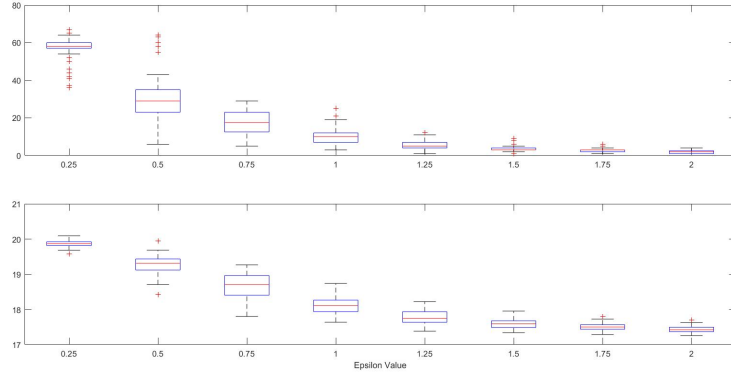


Figure 3: In the upper image, the boxplot exhibits the number of groups defined by different fitness in the network according to the epsilon. The lower image, the boxplot exhibits the average number of edges dying per period. The simulations were performed with a population of 80 edges, 10 shocks per period, $\alpha = 0.99$ and initial fitness drawn from a standard normal. The size of ϵ is strongly determinant on both measures.

The parameter a controls the relative strength of the in-group over the out-group. In our simulations it was set equal to 0.01. Some graphs generated using this variation are shown in figure 4c and figure 4d, with the same parameters used in figure 4a and 4b.

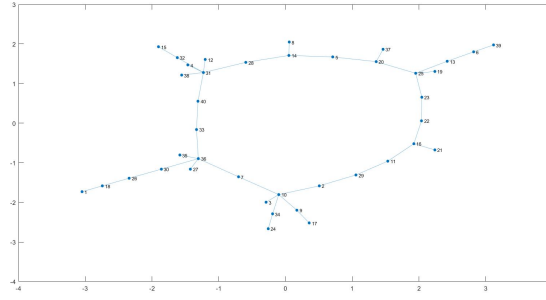
The literature on communication indicates more polarization over time based on networks and alternative media [15]. This model may be used to explain this phenomena. Social niches are built, but people do not communicate with other the way they need to produce stability. This is analogous to what is called liquid modernity [4], but developed in a simpler way by adding equations and taking out a lot of words.

4 Conclusion

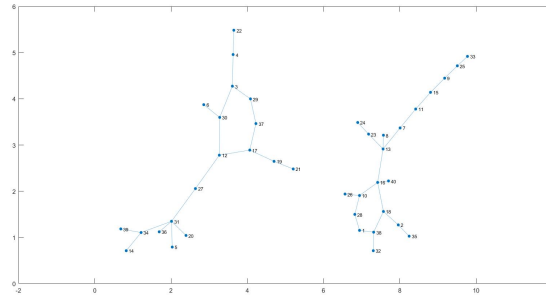
Social networks are an important topic of research. Much is explored in opinion diffusion about imposing communications over networks, but little is done on how communication affects networks. In this paper, this gap is explored and two models which have direct applications on sociological and psychological topics are developed.

The evidence about extroversion being not sufficiently strong to explain social network size when considering age [30] may be studied in the first model. In this analysis, the number of interactions, or age, is determinant for both extroversion and network size.

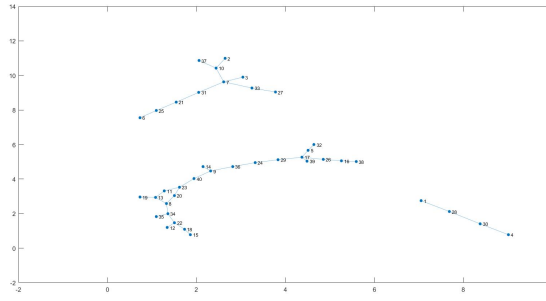
The second model deals with the possibility of some networks being able to adapt and break the formation of large groups because of individual low disposition to communication. This is not a novelty in the sense bounded confidence models [22] already displayed some similar properties. However, to study communication over a static network ignores the stability of groups as dependent of



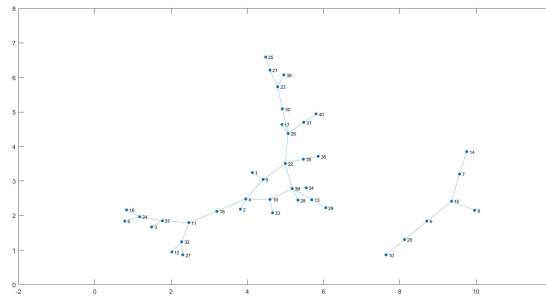
(a) $\epsilon = 0.5$ and using Eq. 2a



(b) $\epsilon = 1.5$ and using Eq. 2a



(c) $\epsilon = 0.5$ and using Eq. 2b



(d) $\epsilon = 1.5$ and using Eq. 2b

Figure 4: Some sample graphs generated using the algorithm proposed. There are an interaction of ϵ and the relative power of in-group and out-group to isolate tribes as can be seen comparing image 4a-4b and 4c-4d.

the willingness to communicate. The new model illustrate this with applications to group dynamics.

Finally, future research in the quantitative stream may include analyse the impact of psychological profiles, such a tendency to be an extremist [13] and emotions [32], and the structural consequences of individual random shocks on agents' fitness. Other interesting topic is to generalize the base network model from a Barabasi-Bianconi network to a more general weighted growth or multicomponent graph model [24].

From a sociological and psychological perspective, to understand the determinants of ϵ across societies and groups is fundamental to comprehend the dynamics of social networks. In political terms, to articulate networks to a comprehensive framework of collective action to explain real phenomena is the next step.

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